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Hedge Funds:
Assets Under Management versus Performance

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ABSTRACT

In this paper we studied the relationship between a Hedge Fund's amount of assets under management and its short-term future performance. The results suggest that the smaller 10% funds in a given period tend to have higher returns in the next months than other bigger funds. There is also evidence that this outperformance arises mainly from skill.

Keywords: hedge funds, assets under management, performance, factors.

DATA TREATMENT

The raw databased used in this study was obtained from EurekaHedge. Of all the tracked funds there, a sub sample was chosen in order to clear the data as much as possible. This data treatment poses as imperative due to the more flexible regulation requirements imposed to the Hedge Fund industry that includes the exemption of full disclosure, making the monthly data, if available at all, less reliable.

First, only the 5264 flagship funds and its correspondent monthly assets under management (AUM) and rate of return (RoR) were selected and only data points from January 2000 onwards were eligible, since there has been a great change in the industry and older periods' patterns barely relate to more recent ones. Regarding those, all the missing AUM points (not the complete data for the fund) were deleted if chronologically this gap was in the extreme point(s) of the time-series (initial and/or final dates). After, only funds that simultaneously had at least 24 months of reported data and no more than one AUM observation missing remained in our sample. For the funds with a single missing AUM value in period t, we interpolated this value, if the adjacent values were not too different, assuming a constant AUM rate of growth between (t-1 ; t) and (t ; t+1) :

$$(1) \qquad AUM_t = \underbrace{AUM_{t-1} \times (1 + RoR_t)}_{\text{AUM}_t \text{ without growth}} \times \underbrace{\left(\frac{AUM_{t+1}}{AUM_{t-1} \times (1+RoR_t) \times (1+RoR_{t+1})} \right)^{\frac{1}{2}}}_{1 \text{ + assumed rate of growth}} .$$

Also, a too constant AUM series represents an evidence of inaccurate report so only the funds with an AUM standard deviation higher than 0.1 and/or with less than 50% of its AUM variation equal to 0% were considered. The last part of the sub-sample selection was assessed more on a case-by-case basis, with the elimination of all the funds that had a reported AUM behavior that seemed unreal and therefore a potential source of distortion in the results (abnormal variations and evidence of bugs in the report, amongst others).

After the imposition of these filters to the AUM data, we analyzed the RoR data. Only 27 points were discarded because they represented abnormal values that could misrepresent the relation under analysis.

The final sample comprises 4432 funds with a total of 356798 AUM points.

DATA EVOLUTION

The evolution of the data from January 2000 to June 2016 is summarized in Graphs 1 and 2.

It is important to highlight that from now on, every time we mention "existing funds", we are not referring to the whole universe of funds that exist in that given period, but rather to the ones that exist and fulfill the aforementioned filters.

In the first three months of 2000 the average figures were: 302 funds, 2.69% of monthly rate of return, 3.45% of monthly flow and about $92 million of assets under management. Since then, the number of funds strictly increased until it reached its peak in the first quarter of 2014, where there was an average number of funds of 2847.

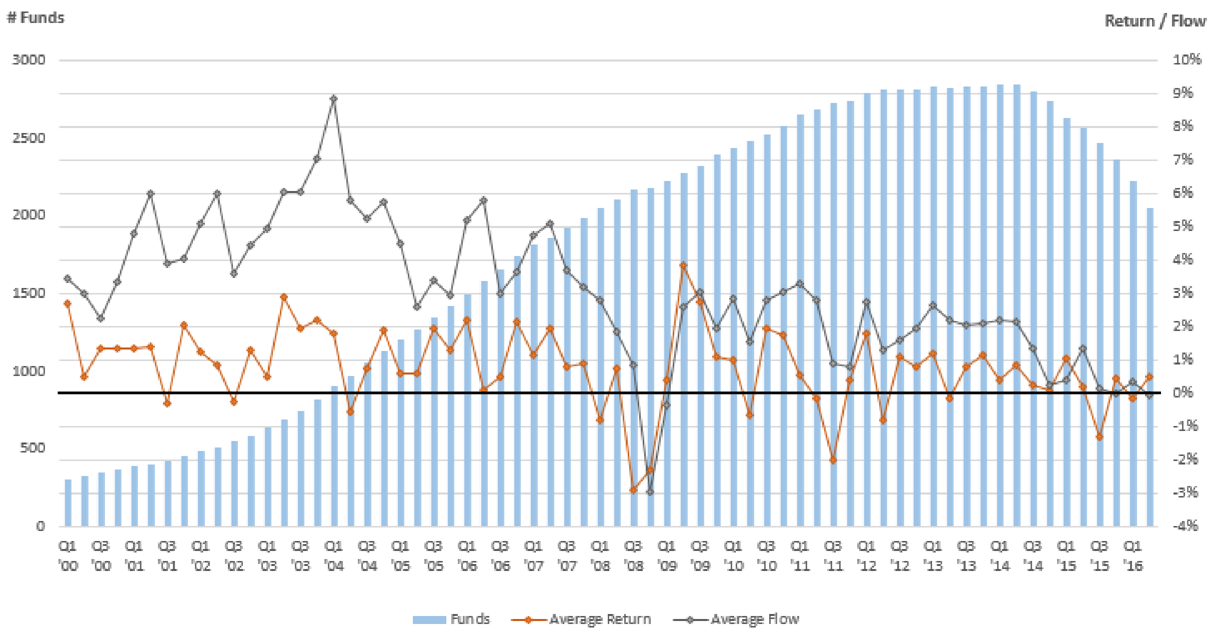
In the last two years of our sample, the tendency has reverted and the number of funds has successively diminished, totaling 2056 in the second quarter of 2016. This growth of 574% was accompanied by a 239% growth in the average AUM level, which amounted to $312 million in the second quarter of 2016.

The path across the years was, however, quite different, with a slide back of about 40% in 2008, amidst the global financial crisis. Both return and flow rates also suffered in this period, reaching their lowest average levels of about -3% for the two.

Since 2011 AUM levels have been escalating and appear to have not been suffering from the recent industry size contraction.

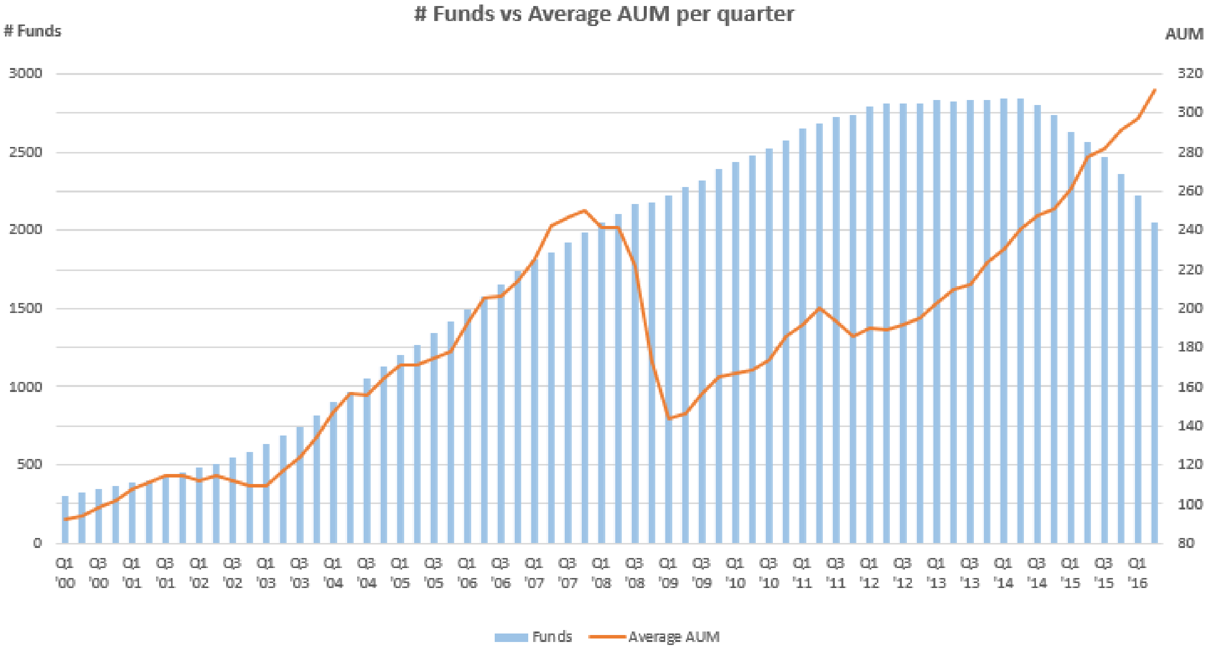
Graph 1:

2000-2016 quarter evolution of number of funds, average monthly return and average monthly flow



Graph 2:

2000-2016 quarter evolution of number of funds and average monthly AUM (in millions of dollars)

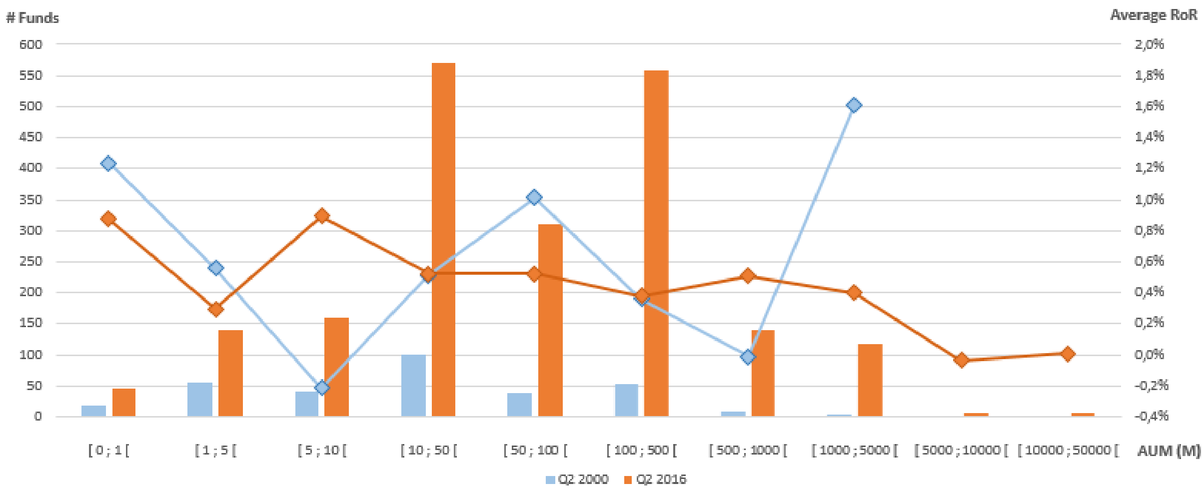


In Graph 3 we have a snapshot of the industry reality in two different points in time – 2000 and 2016's second quarter – from an AUM size perspective. We have divided the universe of funds into ten different buckets, according to their absolute AUM value (in millions of dollars). As seen before, in 2016 there are more and larger funds, with the majority of them reporting an AUM ranging from 10 to $50M in both years.

It is not sensible to draw a conclusion from the RoR values, at least at this point, since this is a highly volatile and unpredictable parameter, as shown in Graph 1.

Graph 3:

Q2 2000 vs Q2 2016: funds' distribution and average return per AUM bucket



FLOW: METHODOLOGY AND RESULTS

Once having the relevant and cleaned data to work with, our aim was to study a possible relationship between a fund's flow in a given month (t) and:

A) its performance in the next month (t+1);

B) its cumulative performance in the next three months (t+3).

Firstly, let us define the concept of flow:

$$Flow_t = \frac{AUM_{t+1} - AUM_{t-1}(1+RoR_t)}{AUM_{t-1}} \quad . \tag{2}$$

If this value is positive then the fund experienced an inflow of money, increasing its assets above the increment due to performance. If it is negative then investors withdraw some money. Although this formula is correct in theory, and despite having neutrally cleaned the data as much as possible, there were still some funds with (less than 50%) of constant AUM points. In those situations, the consequence is having a flow symmetric to the return ($Flow_t = -RoR_t$), which makes the correlation between the two closer to -1, a likely unrealistic value. What we see as a good explanation for this is a misrepresentative report in the sense that there was an absence of flow, not AUM variation. Therefore, in those cases, the assumption made was flow equal to 0%.

Concerning the performance of the fund, it is measured in case:

A) by its reported rate of return for the next given month (RoR_{t+1});

B) by its cumulative rate of return in the next three months:

$$CRoR_{t+3} = (1 + RoR_{t+1}) \times (1 + RoR_{t+2}) \times (1 + RoR_{t+3}) - 1 \, . \tag{3}$$

In some cases we may refer to this rate on a monthly basis, in order for it to be more easily compared with the one from case A):

$$MRoR_{t+3} = (1 + CRoR_{t+3})^{\frac{1}{3}} - 1 \quad . \tag{4}$$

Case A)

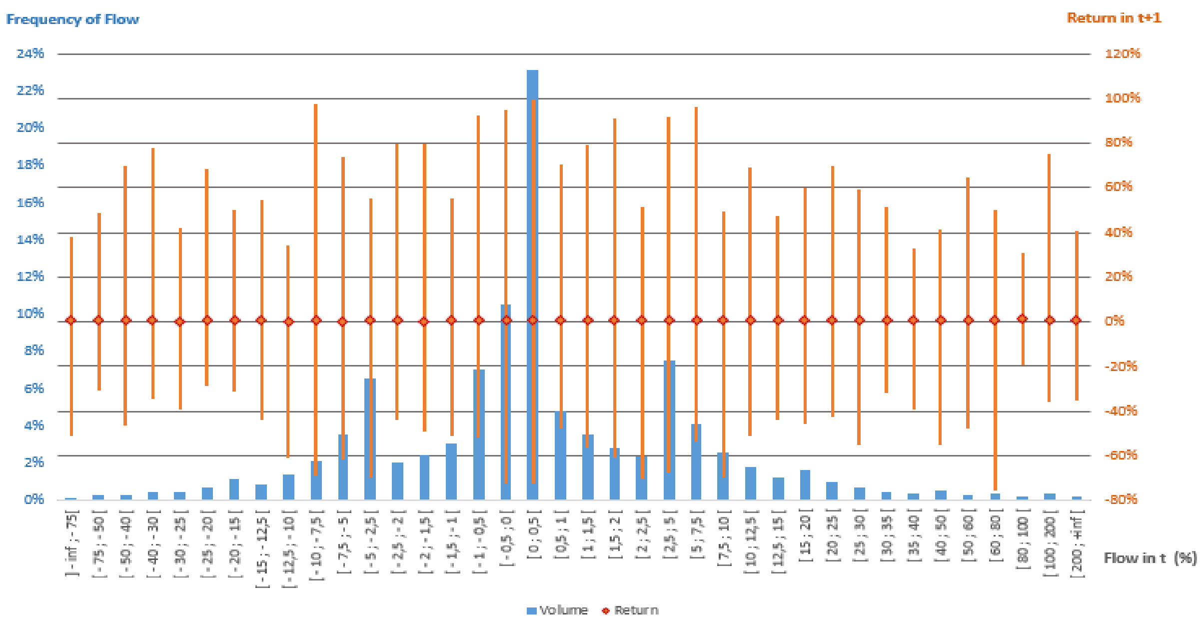
Since the value of the flow is a percentage, we can compare the values over time without standardizing them. Our approach was to organize pairs of (Flow $_{t}$; RoR $_{t+1}$) for each fund and then allocate each pair to one of the 38 buckets constructed based on intervals of flow. Graph 4 illustrates the distribution of these buckets as well as individual maximum, minimum and average RoR $_{t+1}$.

The most common range of flow observed from 2000 to 2016 seems to be between 0% (inclusive) and 0.5% (exclusive) accounting for almost a quarter of the observations. However, note that our previous assumption of setting to 0% all the flows symmetric to RoR and with 0% AUM variation, changed 9.4% of data points. Nevertheless, even if all those points were not 0% indeed, that bucket would have had, in the limit, about 14% of frequency – still one of the largest slices of the cake.

The span of returns is also highlighted in the Graph 4, showing that there is not a clear link and returns can assume extreme values no matter the level of flow.

Graph 4:

Buckets per flow level: frequency and next month average, maximum and minimum return



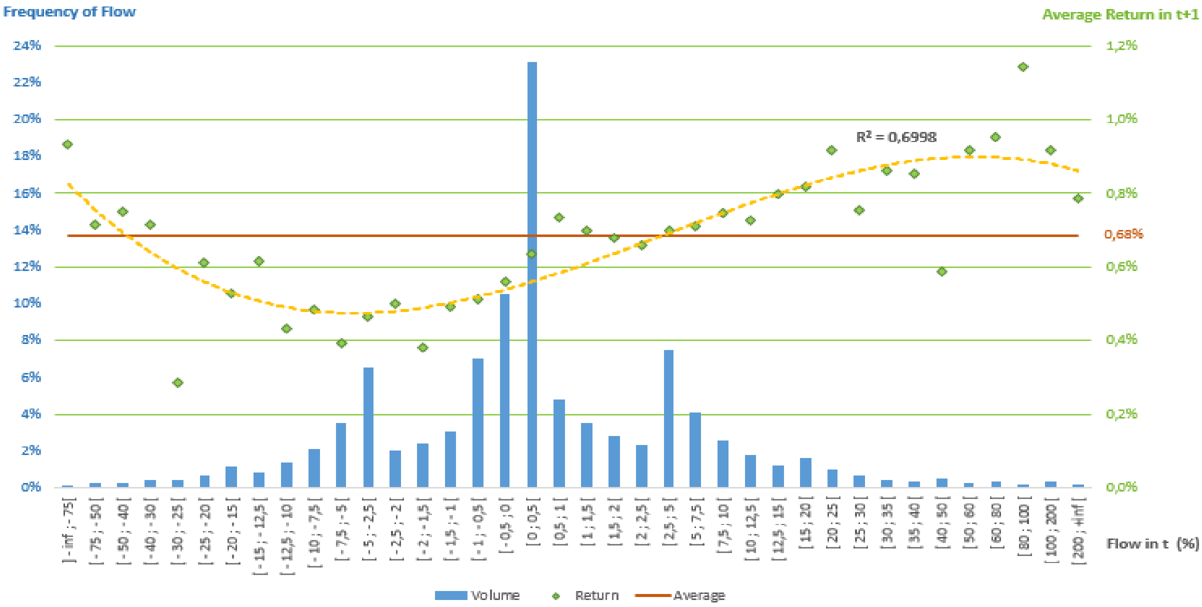
The central question was then challenged: is there any relationship between the level of flow in a given period and its return in the next period? Our analysis suggest that yes, there is an inflection point (which coincides with the average return of all buckets, 0.68%), between 2 and 5% of inflow, with the convex shape in the left tail and the concave shape in the right tail. This fitted curve of degree 3 has a 0.7 R-squared.

In a further comprehensive analysis, the evidence is that funds that face drastic outflows tend to perform in the next month above the 0.68% average for all funds. This outperformance diminishes as the outflow is smaller, reaching its minimum return around 0.5%, on average, for flows between -10 and -2%. After this level, the relationship tends to be positive: the bigger the flow, the higher the return in the next period, up until 0.9% on average. This tendency seems to mitigate when funds suffer extreme inflows (above 100%).

These conclusions can be seen in Graph 5.

Graph 5:

Buckets per flow level: frequency and next month average return with fitted polynomial curve



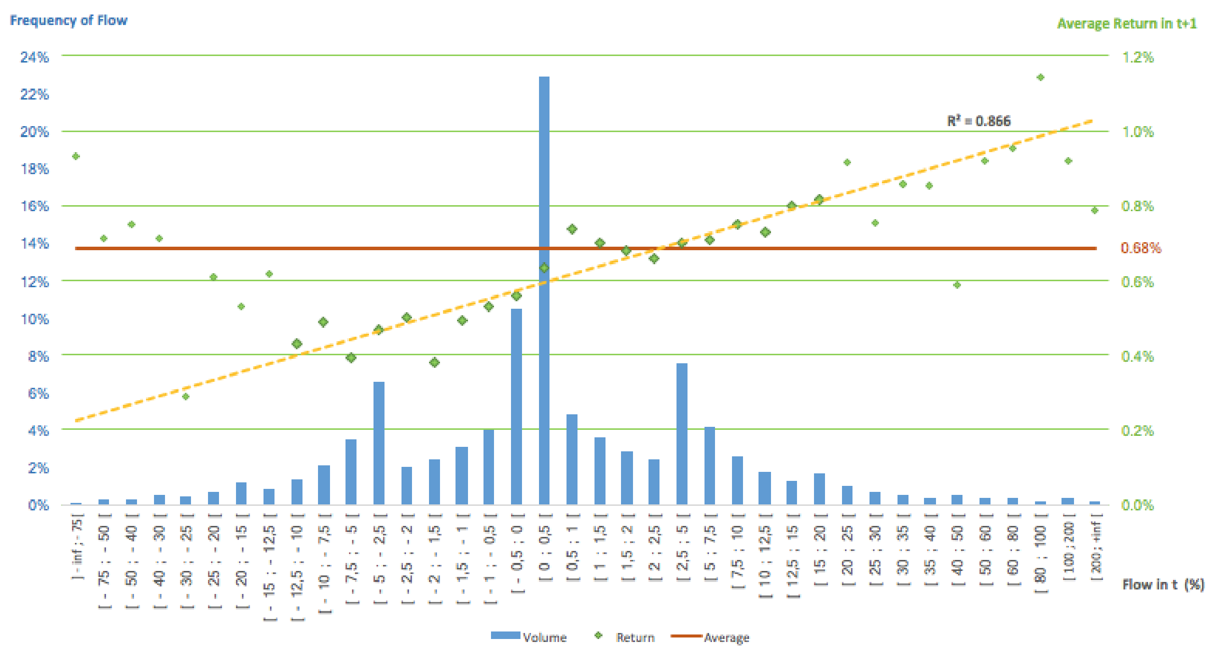
Despite the strong R-squared value of the previous analysis, the relevance and probability of overfitting of the fitted model can be questioned. For the sake of simplicity, we also modelled a sub-sample of the data, which results from the exclusion of flow points in both tails. More specifically, only 4.26% of the all the observations embodied flows below -12.5% and only 4.56% corresponded to flows equal or above 20%, thus deemed to be statistically not significant.

The results are in Graphs 6 and 7, the latter being an additional scrutiny of the next month return dispersion through its monthly average standard deviation per bucket of inflow.

The results suggest a clear positive linear relation, with bigger levels of flow resulting in higher returns in the next month. On the other hand, although weaker, there is evidence of a linear decreasing relation between the level of flow today and the standard deviation of the next month return. These two conclusions together support the thesis that the bigger the flow today, the better the performance will be in the next month, at least for the range -12.5 to 20% of flow.

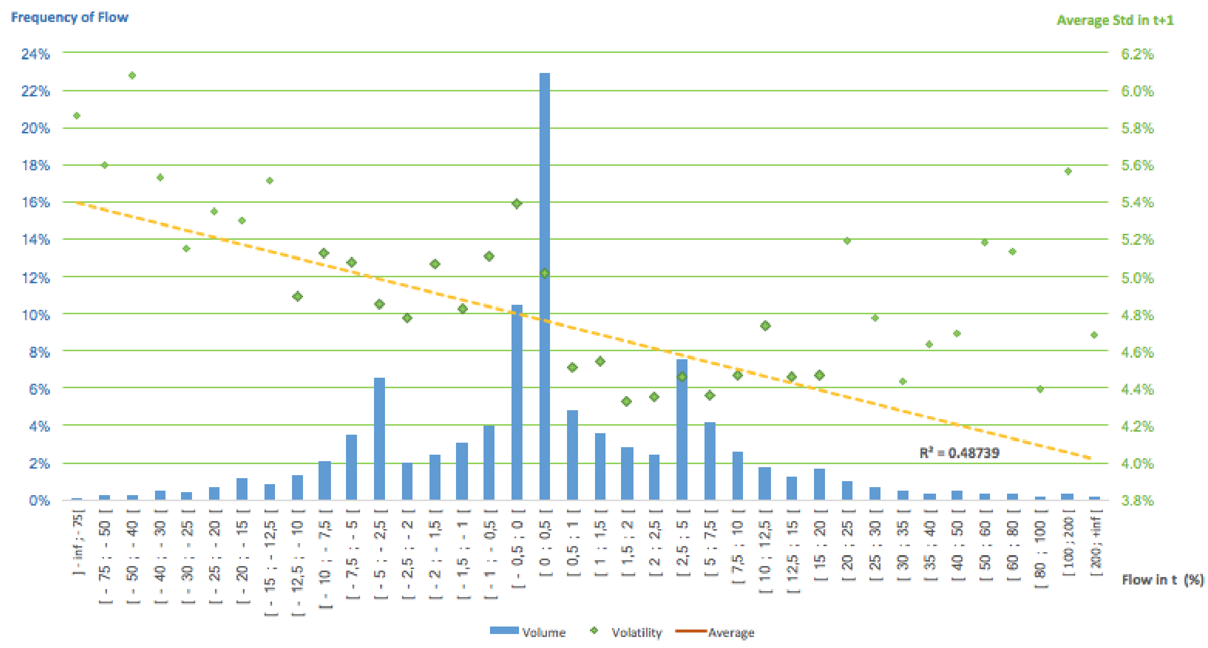
Graph 6:

Buckets per flow level: frequency and next month average return with fitted sub-sample linear curve



Graph 7:

Buckets per flow level: frequency and next month average standard deviation of returns



<u>Case B)</u>

The rationale and methodology behind case B) was the same as in case A), but with the relation under analysis being the level of flow in a given period versus the cumulative return in the next three periods.

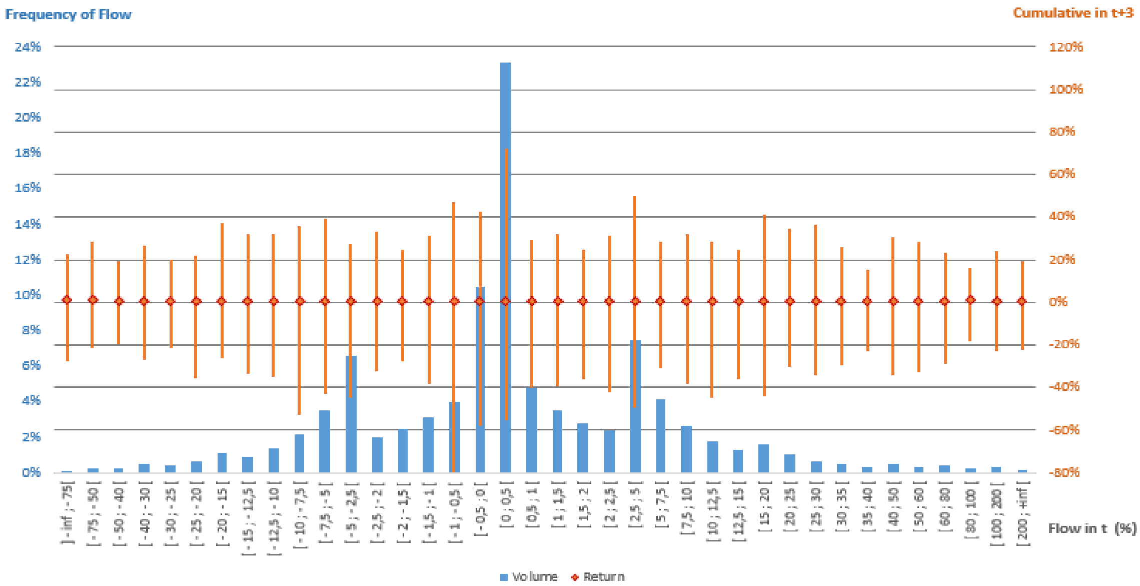
Analogously to Graph 4 we plotted the same buckets' distribution and the individual maximum, minimum and average cumulative RoR $_{t+3}$ in monthly figures in Graph 8.

In this case, the span has shrunk and the returns' extreme values seem a lot more constant, with maximums around 30% and minimums -36%, again, per month.

A similar conclusion was drawn with respect to the main question: how does a given level of flow impact the performance over the next three months? As in case A), this relationship is best described through a curve of degree 3, having an even higher evidence of goodness of fit, with a 0.81 R-squared. All the main characteristics of the fitted curve (Graph 9) remained the same; the average return across all buckets is 0.69% (or 2.09% cumulative in three months), one basis point above the next-month return of case A), and this value coincides again with the inflation point. Also unchanged are the intervals of flow that correspond to the minimum and maximum average return for the next three months, from -10 to -2% and from 40 to 60%, respectively. Once again, similar conclusions were drawn from the sub-sample analysis (4.18% of observations with less than -12.5% flow and 4.63% with flow equal or above 20% discarded), as can be seen in Graphs 10 and 11.

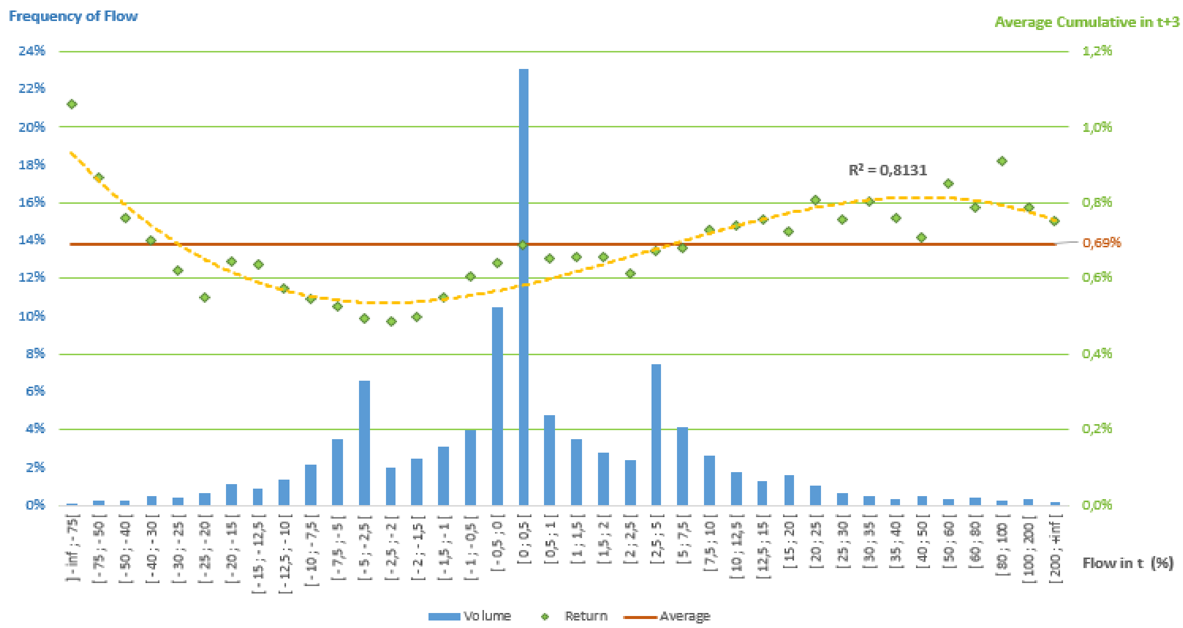
Graph 8:

Buckets per flow level: frequency and next 3-months average, maximum and minimum return



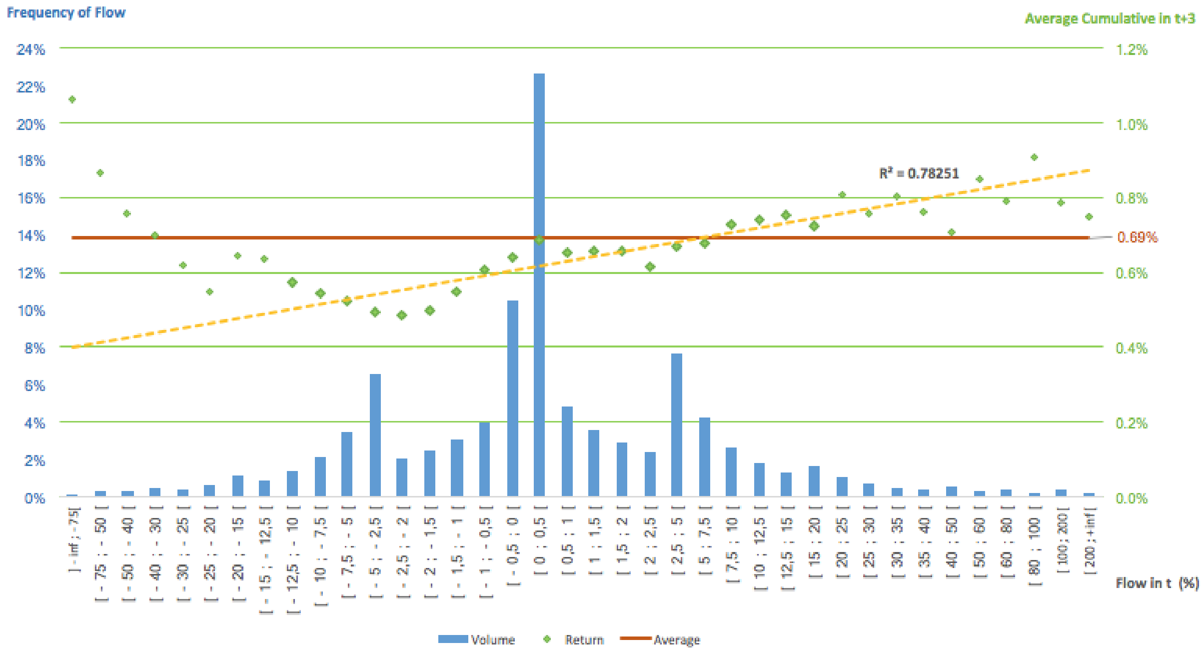
Graph 9:

Buckets per flow level: frequency and next 3-months average return with fitted polynomial curve



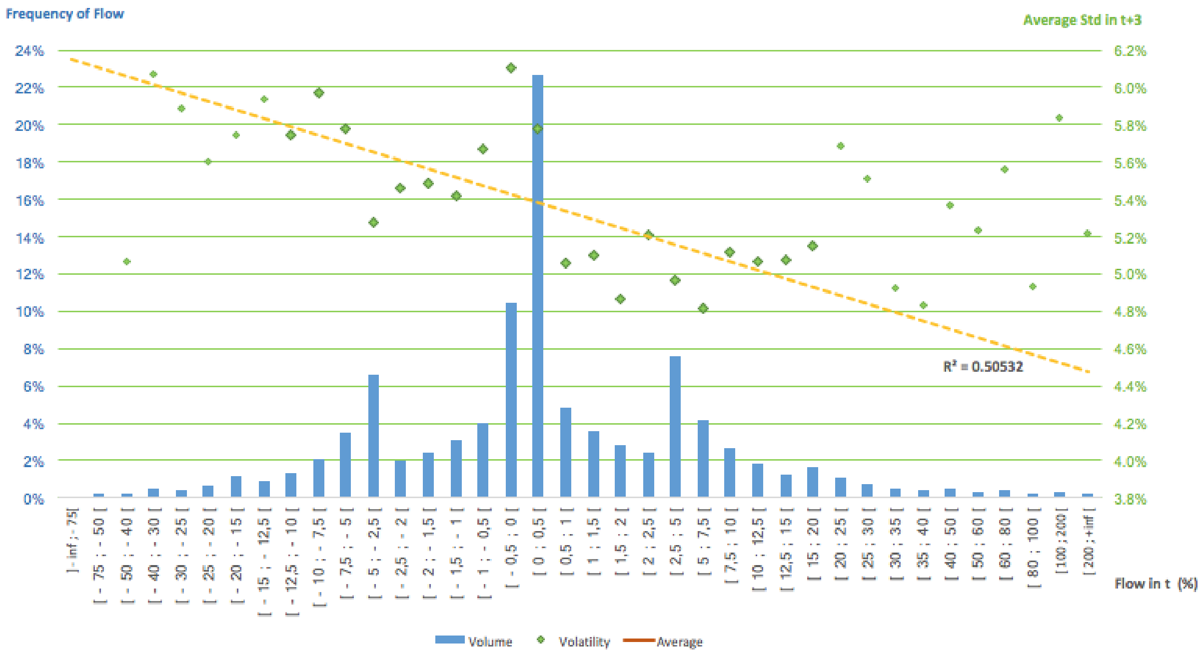
Graph 10:

Buckets per flow level: frequency and next 3-months average return with fitted sub-sample linear curve



Graph 11:

Buckets per flow level: frequency and next 3-months average standard deviation of returns



What this similarity between case A) and B) suggests is that not only seems to exist a relationship between flow today and performance in the next month but there is also evidence of persistence of that relation throughout the subsequent three months.

ASSETS UNDER MANAGEMENT: METHODOLOGY AND RESULTS

The last and main question to address is whether the absolute value of the assets under management (AUM) of a fund has an impact on the fund's performance or not.

In contrast to the last covered topic in which we had a relative value – a fund's monthly flow – that therefore we could analyze throughout the years without any standardization needed, we now face an additional problem. As seen in the "Data Evolution" section, the Hedge Fund industry has developed in a continuously changing environment. The standard today is not the same as it was fifteen years ago. For instance, the maximum AUM in our sample in January 2000 was $2.6B and by January 2016 it was $15.7B. And this difference in scale had to be accounted for.

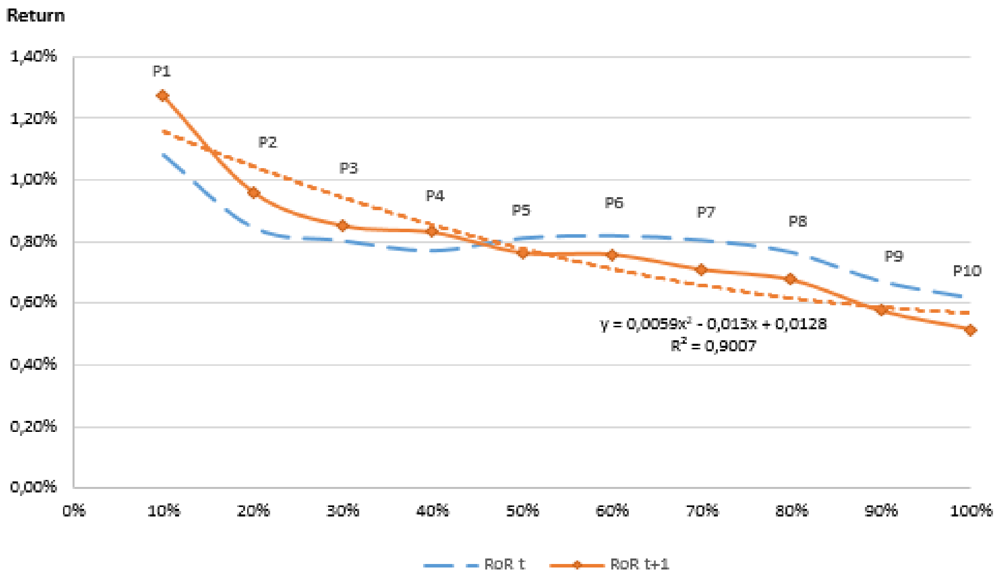
The solution we have decided to implement was to rely on deciles. In each of the 200 months (January 2000 to August 2016) we split the existing funds into 10 portfolios; portfolio P1 including the smallest 10% funds and P10 the largest 10% funds. Whenever the total number of funds were not divisible by 10, we allocated the "excess" funds randomly so that each portfolio would have at maximum one more fund than the portfolio with the least number of funds. Also, when there was more than one fund with an AUM value in the endpoint of the decile, the allocation was random. After this reorganization of the sample we fulfilled the conditions necessary to compare funds' returns across the months based on their AUM level.

Our first approach was to compare the return a fund had today, with a given AUM, and the return that, with that level of AUM, the fund was able to generate in the next month. Our results show that up to P4, this is, the 40% smallest funds in each period, the return is on average bigger in the next month. P1 funds add, on average, 0.19% to their previous month return.

The additional return however decreases as AUM increases, and for the 60% top-sized it even gets negative, with returns in the next month being, on average, lower than todays'. P10 funds worsen their return in 0.1%, on average. Furthermore, this tendency persists for the next 3 and even 6 months. Instead of comparing the return of the next month with today's return, we can also look to the moving average of the last 3 months. The results are the same, supporting the thesis that smaller funds tend to perform better, at least in the near future. All these conclusions are illustrated in Graphs 12, 13 and 14.

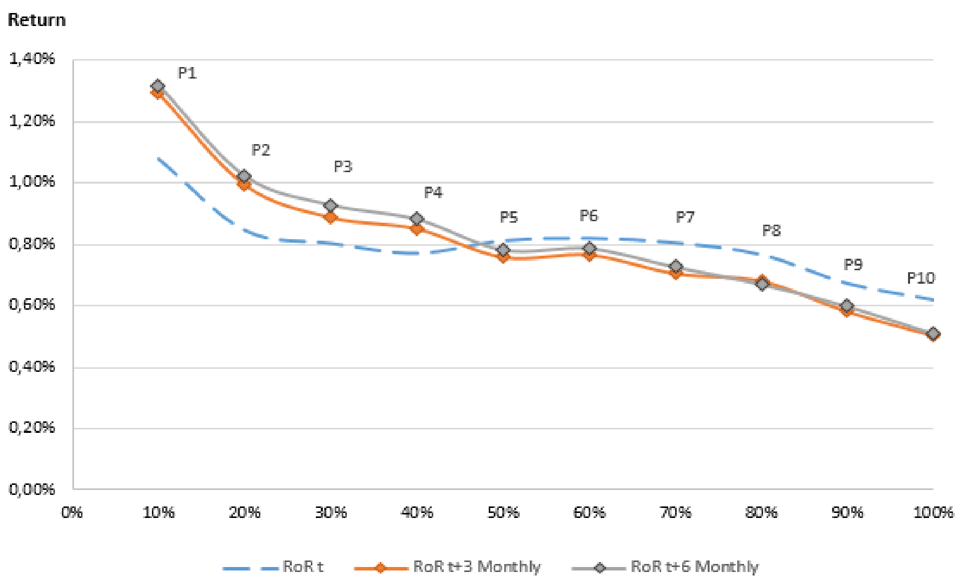
Graph 12:

Return today versus next month return per portfolio



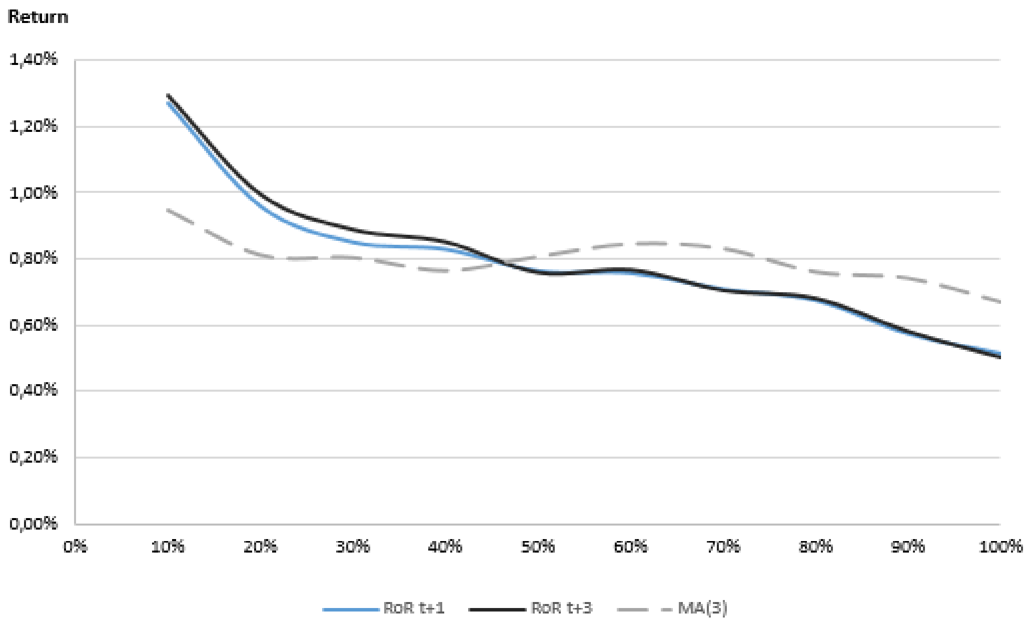
Graph 13:

Return today versus next 3 and 6 months return per portfolio



Graph 14:

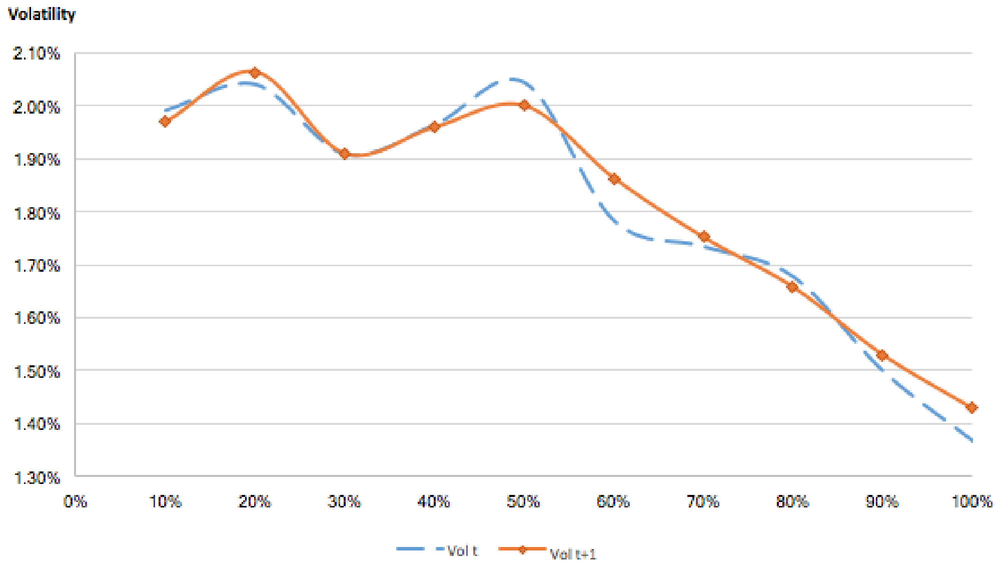
3-Month moving average versus cumulative return in 3 and 6 months (monthly figures) per portfolio



Looking at the returns does not give us a full picture of the portfolio performance, especially if we intend to define an investment strategy based on this analysis. To enrich our understanding, we also computed the average monthly standard deviation of the returns per portfolio, a key measure for a risk/return analysis. Observing Graph 15 it is evident that the higher returns for the smaller portfolios come at the expense of higher volatility. P1 has almost 2% of monthly volatility while P10 downed this number to approximately 1.4%. For the 50% largest portfolios, volatility strictly decreases with the size. One qualitative explanation may be that bigger funds are more diversified and/or perhaps do not invest in risky assets, preferring instead more safe and lower “certain” return, while the smaller funds bet on risky assets in an attempt to increase their AUM other than gathering money from investors, which is usually difficult for smaller funds and may take more time than desired.

Graph 15:

Return's volatility today and in the next month, per portfolio



After our findings, we had one last question: where is this outperformance of the smaller funds coming from? Is it the result of a pure alpha or a higher market exposure?

To try to answer, we set two simple multi-factor models, model A) and B).

The beginning of this process was to gather a set of macroeconomic financial variables and test them with different permutations until we were in the presence of a good model. And by "good model" we mean one with a decent explanatory power but most important not at the expense of statistical complexities such as multi-collinearity. We paid special attention to such details as financial variables frequently have substantial correlations that, if not properly dealt with, may adversely affect the robustness of the model. We also privileged the statistical significance of each variable as much as possible to ensure that the final set of factors was comprehensive not only jointly but also individually.

Of all the variables tested, including indicators for equities, credit, interest rates, derivatives, currencies and volatility, we were left with only two, a simplistic but more reliable model.

For the market component, S&P500 (SPX) was the chosen factor, as it proved its widely recognition of being the best benchmark. The other, the ICE 1-month US dollar Libor (US0001M), represents the short-term interest rate level, and was picked instead of the Overnight Index Swap rate (which might be a better proxy for the risk-free rate) because its statistical results were better.

Another factor was also considered but we will turn into that at a later stage.

For now, we will focus on model A):

$$RoR_t = \alpha + \beta_1 * Libor\ 1m_t + \beta_2 * S\&P\ 500_t \quad . \tag{5}$$

This two-factor model tries to identify and weigh the sources of return, for each portfolio. The eligible sources are the previously reviewed Libor and S&P levels, as of today, but also another element that we have not discuss yet: alpha.

In fact, it is the single most important variable under analysis. Alpha represents the portion of the return that is not explained by the other variables. In a perfect world, where we could define the model in all its completeness, alpha would solely represent skill-based return. That is why the Hedge Fund industry is known for its quest for alpha.

In Table 1 we have summarized the results for model A). The first evidence is that, at a 5% significance level, all coefficients for all portfolios are statistically significant and our model explains 40% or more of the variation of RoR in all portfolios except P10 (the largest 10% funds) where only 33% is explained. At this point we can start to analyze the values with some sense of reliability.

Table 1:

Model A) results per portfolio: R-squared, coefficients and p-values

	R^2	Alpha		Libor 1 month		S&P 500	
		Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
P1	0,51	0,75	0,00	2,61	0,00	0,32	0,00
P2	0,58	0,47	0,00	2,30	0,00	0,36	0,00
P3	0,46	0,42	0,00	2,06	0,00	0,30	0,00
P4	0,53	0,34	0,01	2,38	0,00	0,33	0,00
P5	0,52	0,35	0,01	1,90	0,00	0,34	0,00
P6	0,49	0,30	0,02	2,22	0,00	0,30	0,00
P7	0,51	0,26	0,03	2,20	0,00	0,29	0,00
P8	0,46	0,31	0,01	1,76	0,00	0,26	0,00
P9	0,41	0,28	0,02	1,38	0,01	0,23	0,00
P10	0,33	0,25	0,03	1,26	0,01	0,19	0,00

Since all the values in the model are in percentage and expressed in monthly figures, we can directly compare and decompose the different components. However, the absolute value of the coefficients of different factors does not provide an explicit conclusion by itself because different factors have different scales (Libor is not expected to return the same as S&P) so it is normal that factors with lower averages face bigger coefficients.

To effectively compare each source of return, we computed average numbers for each portfolio, as seen in Table 2, and it is on average terms that the subsequent analysis will be made.

Starting with the exposure to the market, all portfolios seem to face the same approximate beta, which is about 0.3, contributing monthly with 0.09% on average. The portfolio containing the 10% largest funds in each period is the one that, according to our results, is less exposed to the market, with just 0.19 beta, suggesting that top-sized funds favor diversification in their strategies at a greater extent.

On the other hand, the interest rate level has a less constant impact across all portfolios, with a clear decreasing tendency of impact. The smallest 10% funds are by far the ones more exposed to 1-month Libor risk, with 0.43% of the return coming from it.

Lastly, alpha. And here it becomes clear what the source of outperformance of the smallest funds is: they are able to generate a much bigger alpha. P1's alpha amounts to 0.75%, a value bigger than the total return of the 40% largest funds. Although at a more modest level, P2 and P3 also deliver a good alpha.

Table 2:

Model A) average return decomposed per source

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Alpha	0,75%	0,47%	0,42%	0,34%	0,35%	0,30%	0,26%	0,31%	0,28%	0,25%
Interest Rate	0,43%	0,38%	0,34%	0,39%	0,31%	0,36%	0,36%	0,29%	0,23%	0,20%
Market	0,10%	0,12%	0,09%	0,10%	0,11%	0,10%	0,09%	0,08%	0,07%	0,06%
Total	1,27%	0,96%	0,85%	0,83%	0,77%	0,76%	0,71%	0,68%	0,58%	0,52%

We ended our study with model B):

$$RoR_t = \alpha + \beta_1 * Libor\ 1m_t + \beta_2 * S\&P\ 500_t + \beta_3 * HF\ Index_t \quad . \tag{6}$$

In this model we added another factor to model A), Hedge Fund Index which is “a measure of the average return of all Hedge Funds (excepting Funds of Funds) in the Barclay database. The index is simply the arithmetic average of the net returns of all the funds that have reported that month”.

What we sought to assess by running this regression was the “alpha in excess of industry alpha”. This is, considering the returns the Hedge Fund industry as a whole delivered, how much of the alpha generated is just in line with those values and how much is an extra return above the Hedge Fund industry average and thus reinforces the thesis of management skill, for a given portfolio?

In Table 3 we have the coefficients and their p-values. First of all we should look to the coefficients of the factors in common with model A), Libor and S&P. They still are statistically significant at a 5% confidence level but most important the values remained practically unchanged, supporting the modeling and conclusions of model A).

In respect of alpha, the situation is very different. By adding the new factor it is as if the alpha had been split into two components so that:

(7) $$\alpha_{\ Model\ B)} = \alpha_{\ Model\ A)} - \ \beta_3 * HF\ Index_{\ t} \quad ,$$

And this is why we called it an “extra alpha”, above the industry one.

By looking at the results, this new alpha is not statistically significant for the 70% largest portfolios, suggesting that they just perform as a Hedge Fund “should” and there is no extra alpha.

The 30% smaller portfolios are the ones which outperform not just the market and interest rates but even the Hedge Fund universe. P1 even strengthens our previous conclusions that the smaller funds tend to perform better by being the only portfolio that simultaneously has a zero p-value for its alpha and a clear statistically evidence of lack of significance towards de HF Index. This could be interpreted as follows: small funds thrive because of skill.

In Table 4 we have again a breakdown of the returns per source. The portfolios containing the extreme amounts of AUM, P1 and P10, are the least sensitive to the industry, others absorb on average 0.08%.

P1 is still clearly the portfolio that delivers more alpha, 0.73%, down by just two basis points.

The main conclusion of this study gains momentum: **smaller funds tend, on average, to perform better than bigger funds**.

Table 3:

Model B) results per portfolio: R-squared, coefficients and p-values

		Alpha		Libor 1 month		S&P 500		HF Index	
	R^2	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
P1	0,51	0,73	0,00	2,60	0,00	0,32	0,00	0,04	0,50
P2	0,60	0,40	0,00	2,24	0,00	0,35	0,00	0,16	0,00
P3	0,47	0,36	0,01	2,01	0,00	0,29	0,00	0,14	0,01
P4	0,56	0,26	0,05	2,31	0,00	0,32	0,00	0,17	0,00
P5	0,55	0,27	0,05	1,83	0,00	0,33	0,00	0,18	0,00
P6	0,51	0,24	0,07	2,17	0,00	0,29	0,00	0,14	0,01
P7	0,55	0,18	0,14	2,13	0,00	0,28	0,00	0,19	0,00
P8	0,49	0,24	0,05	1,70	0,00	0,25	0,00	0,14	0,00
P9	0,44	0,21	0,07	1,33	0,01	0,22	0,00	0,15	0,00
P10	0,34	0,21	0,08	1,22	0,01	0,18	0,00	0,10	0,02

Table 4:

Model B) average return decomposed per source

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Alpha	0,73%	0,40%	0,36%	0,26%	0,27%	0,24%	0,18%	0,24%	0,21%	0,21%
Interest Rate	0,42%	0,37%	0,33%	0,38%	0,30%	0,35%	0,35%	0,28%	0,22%	0,20%
Market	0,10%	0,11%	0,09%	0,10%	0,10%	0,09%	0,09%	0,08%	0,07%	0,06%
HF	0,02%	0,09%	0,07%	0,09%	0,09%	0,07%	0,10%	0,08%	0,08%	0,05%
Total	1,27%	0,96%	0,85%	0,83%	0,77%	0,76%	0,71%	0,68%	0,58%	0,52%